Revolutionizing Diabetic Retinopathy Screening for early vision preservation by integrating Convolution Neural Network

POOJA A[1], DHANANJAYA V[2]
[1]Department of Computer Science & Engineering
Impact College Of Engineering & Applied Sciences,
Affiliated by VTU
Bangalore,
INDIA

[2]Department of Computer Science & Engineering
Impact College Of Engineering &
Applied Sciences,
Affiliated by VTU
Bangalore,
INDIA

Abstract: — Diabetes is one of the increasing serious health issues, affecting millions of people. Consequently, the greater portion of individual is affected by diabetes, some of the related issues such as cardiovascular disease, kidney failure, nerve damage, foot problems and vision problems are growing rapidly. Diabetic retinopathy (DR) is a severe complication of diabetes and a leading cause of preventable blindness worldwide. Early detection requires expert evaluation of retinal fundus images, but limited access to specialists delays diagnosis. This work presents an automated DR screening pipeline using pertained Convolutional Neural Networks (CNNs), including VGG16, VGG19, and ResNet50, for five-class DR severity classification. Using 3,662 Kaggle fundus images with systematic preprocessing, augmentation, and class balancing, the proposed approach achieves a highest accuracy of 96.3% and F1-score of 0.898. The model supports improved early diagnosis by enabling scalable, automated retinal image screeningto enhance primary diagnosis and minimizes blindness risk.

Key-words: — Diabetic retinopathy, eye fundus images, Classification, CNN, VGG16, VGG19, ResNet50 component

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1. Introduction

Diabetes mellitus is increasing globally, contributing to complications such as Diabetic Retinopathy (DR), a progressive eye disease caused by chronic hyperglycemia. Damage to retinal blood vessels results in swelling, leakage, and abnormal angiogenesis, leading to irreversible vision loss if untreated. Early diagnosis through routine fundoscopy is essential, yet specialist shortages hinder timely detection. Deep learning using CNNs enables automated analysis of fundus images, offering scalable early screening solutions. It is intent that significant of sugar in the blood sustained increase in glucose concentration levels can lead to damage in the minute blood vessels of the retina, which is light-sensitive area located at the posterior of the eye. Diabetes can cause swelling of retina, leakage of fluid, abnormal blood vessel proliferation causing temporary or permanent visual impairment if untreated [1]. The Diabetic Control and Complications Trail (DCCT) emphasizes that strict blood sugar control decreases the possibility of DR and delays its progression in type-1 diabetes. For type-2 diabetes HbA1c levels should be <6.5% which is essential in optimizing the disease outcome [1, 2]. Hence, active diabetic management including optimal blood sugar control, regular ophthalmic examination and timely intervention is required for preventing and altering the disease progression. Automated diagnostic strategies are pivotal in achieving this and reducing the end organ damages due to diabetes [2]. The research introduces an innovative multistage transfer learning strategy that combines three distinct CNN architectures—EfficientNet-B4, EfficientNet-B5, and SE-ResNeXt50—to improve DR classification, by integrating these models into an ensemble framework, the approach capitalizes on their complementary strengths [3].

The study investigates how transfer learning and fine-tuning pre-trained models can improve classification performance, mainly while dealing with small datasets. By leveraging pre- trained models, researchers can capitalize on the extensive knowledge on these models, which have gained from large- scale datasets, such as ImageNet, and adapt them to specialized tasks like DR systemization. The representative shown an outstanding evaluation in performance in identifying healthy eyes, achieving an F1 score of 0.97. This highlights the score indicating excellent precision and recall, reflecting the model's ability based on accuracy to distinguish healthy retinas from those affected by DR [4]. The model effectively categorized Diabetic Retinopathy into four distinct levels, demonstrating robust performance with a Cohen's Kappa score of 0.8836 on the validation dataset [4].

The objective of the research determines the enhancing image preprocessing and ensuring dataset quality significantly contribute to higher accuracy in DR prediction. Ensuring high-quality data preprocessing and dataset integrity is key to optimizing machine-learning models, letting them to emphasis on learning essential and representative features. [5, 6]

By utilizing pertained models of CNN assistances in refining feature extraction, VGG16 and InceptionV3 improve the robustness of DR detection systems, enabling swift identification of abnormalities with a strong emphasis on minimizing false negatives. This ensures that fewer cases go undetected, consenting for more active management and treatment planning. It improves early detection, enabling meticulous treatment planning and better patient outcomes [6], The proposed research examines several classifiers to identify the optimal method for DR lesion detection and grading. It focuses on hierarchical severity level grading (HSG) system notifies the challenges in retinal segmentation, pathology identification and DR severity classification detection using supervised algorithm. Hence, this technique enhances the improvement in accuracy and validates the computational time by comparing with advanced techniques [7].

The study highlighted to address the complication that is detection of small blood vessels with in ocular images that are frequently hidden by noise, which is one of the critical challenges in diagnosing diabetic retinopathy such that advanced image processing techniques and CNN architectures will be employed. The research aims to detect diabetic retinopathy at early stage using OCT scans by intending a CAD system for automatic segmentation of retinal layers by evaluating the system performance against state-of-the-art deep learning networks by achieving accuracy over 94% [7]. Emphasizing the importance of image preprocessing steps like contrast adjustment, denoising, and segmentation, along with dataset quality, the study discloses their impact on boosting the prediction accuracy of DR detection models. By using data dimension reduction, the superiority of input images and safeguarding datasets are comprehensive and well structured, researchers can significantly expand the staging of statistical learning [8]. The research concentrates on enhancement of active images using Gaussian filtering, which reports the imbalanced dataset samples significantly enhances model performance by grouping different levels of diabetic retinopathy, this can be done by providing a complete channel for processing and analyzing a retinal fundus image [8,9]. The study uses advanced image processing techniques and CNN architectures are employed for improvement in detection of DR and by applying transfer learning model and fine-tuning with the ResNet18 architecture that make use of knowledge about pre-trained models obtained from large- scale datasets [9].

Hybrid Network: Combines VGG16 as the feature extractor with XGBoost as the classifier to leverage both deep learning and gradient boosting strengths for enhanced performance. DenseNet-121: Utilizes Dense Net's efficient feature extraction and dense connectivity to further improve DR detection accuracy using DenseNet121 [14].

Findings from the study show that 75.6% of the participants had Type 2 diabetes, making it more prevalent, while only 7.8% were diagnosed with Type 1 diabetes. The interruption underscores the significance of tailoring DR management strategies to the unique needs and risks of both diabetes types [15].

The research uses Efficient Net models for validating the strength by signifying its effective applications in diabetic retinopathy severity classifications in the real world by specifying a selective training data and proper loss functions, to improve predictions for fast diagnosis in diabetic retinopathy using collaborative approach.

This revised ResNet-50 model embodies important progression in DR detection, highlighting the probable of tailored deep neural network models to improve medical imaging analysis. This enhanced model incorporates several innovative strategies to optimize its performance through image preprocessing, adaptive learning rates and regularization to avoid overfitting [16].

The study advises to avoid diabetic retinopathy progression by monitoring hyperglycemia and dyslipidemia, adversarial effects from treatment such as laser treatment improves vision in diabetic macular edema but increases cataracts risk and raised intraocular pressure were remarked, the protective properties of exosomes from retinal astrocyte cells in contradiction of retinal vessel leakage [17]. A modified ResNet-50 framework aimed at optimizing DR detection and classification. The research emphasizes on the significance of biomarkers, such as retinal biomarkers and extracellular vesicles (EVs), in advancing the early detection and progression assessment of diabetic retinopathy. The consistent evaluation is done in both early and advanced stages of DR, EVs from platelets and monocytes demonstrate elevated levels, paving the way for novel approaches to disease monitoring [18].

2.Literature Survey

Yoshihiro Yonekawa et.al [1] The research underscores the relationship between hyperglycemia and DR, as demonstrated by the Diabetic Control and Complications Trial. It emphasizes on anti-VEGF therapy with traditional treatments for monitoring diabetic retinopathy, clinical trials identify significant anatomical benefits from anti-VEGF therapy in NPDR without diabetic macular edema importance of glycemic control and cardiovascular factors in preventing progression of diabetic retinopathy.

Thippa Reddy Gadekallu et.al [2] the objective of the research is to integrate application of principle component analysis and firefly algorithm for dimensionality reduction to enhance accurate predictions, it draws an importance of data pre - processing to improve performance and reduce training time. Borys Tymchenko et.al [3] Projected on multistage transfer learning approach, utilizing an ensemble of CNN architectures, enhances generalization and reduces variance, leading to stable results even with unstable metrics, use of SHAP for feature visualization aids in interpreting model predictions and concludes an automatic deep-learning-based method for detecting the stage of diabetic retinopathy using single fundus photography is effective, achieving a high sensitivity and specificity of 0.99.It highlights the significance of early recognition of diabetic retinopathy to prevent permanent blindness.

Abhishek Samanta a et.al [4] The study explores the effectiveness of transfer learning and fine-tuning on pre-trained models to improve classification performance on real time applications with limited data by classifying different levels helps in early detection and progression of diabetic retinopathy.

P. Saranya1 et.al [6] The study introduces the detection and grading of non-proliferative Diabetic Retinopathy using Convolutional Neural Networks, highlights the significance of image pre-processing methodology includes up sampling/down sampling data and optic disc segmentation for image processing and dataset quality, for better prediction accuracy achieved is 90.89% using MESSIDOR images after pre-processing which highlights the significance of image quality for accurate classification.

Muhammad Samer Sallam, et.al. [7] The research presents a preset system for detecting and classify retinal images into five severity levels using pre-trained ResNet18 CNN with transfer learning. The three-stage pipeline involves image pre-processing, feature extraction and techniques to manage data imbalance. The model achieved with the 70% accuracy, 50% recall, 88% specificity, and an F1-score of 49.5% indicating potential for automatic DR detection, however it shows scope for further optimization.

P. Saranya et.al [8] Optimizing medical image analysis through advanced preprocessing techniques like contrast enhancement. Segmentation is performed using contouring to extract blood vessels, while a CNN based on VGG-16 is opted for attribute extraction and categorization. The Gaussian filter is employed for noise reduction, outperforming the Gabor filter.

Imran Qureshi et.al [9] the research projected on image pre- processing, feature extraction and classification by integrating hybrid approach on distinctive model to enhance diabetic retinopathy detection, highlighted the importance of combining image processing and data-mining techniques for effective fundus image analysis possibly reducing vision impairment in diabetic patients, improving robustness in DR identification. Sagar Suresh Karki et.al, [10] The model utilized OpenCV for preprocessing tasks like radius reduction and image resizing. To improve model generalization, augmentations and contrast adjustments and rotation were applied. Efficient Net, a neural network mainly used for categorizing diabetic retinopathy severity, achieving high accuracy. For classification Decision trees and support vector machines, as classic machine learning approaches are also considered. Efficient Net significantly enhanced image performance, enhancement and classification.

Noor M. Al-Moosawi et.al [11] The research goals at Data augmentation techniques to increase data training samples, explicitly for lower classes, pre-trained models on ResNet34 suggestively improved in performance assessment metrics for the fundus image dataset demonstrating longer feature extraction proficiencies. To address the issues of class imbalance, augmentation techniques were utilized during training process by achieving improvement in classification accuracy of diabetic retinopathy.

Rizq Khairi Yazid [14] To categorize the severity levels in diabetic retinopathy, trained images are resized and converted to grayscale. VGG16 architecture is used for dimensionality reduction, validating the model and evaluating accuracy.

Chun-Ling Lin1* et.al [15] The best investigation of the research is data transformation approaches which is essential to stabilize datasets to upgrade the performance of neural networks in detecting diabetic retinopathy and also prominence on pre-processing methods to improve the quality of retinal images by utilizing dynamic learning rates laterally with regularization methods in order to avoid overfitting, to enhance reduce loss and accuracy.

Cheena Mohanty et.al [16]. The research proposes a hybrid model by integrating VGG16 and XGBoost for feature extraction and classifier respectively, the proportional analysis is achieved by superior outcome over an existing technique to diagnosis diabetic retinopathy for classification and identification, to highlight the efficiency of deep learning model for primary DR detection using DenseNet121 model.

Image background removal using REMBG suggestively better-quality model performance by better distinctive and categorizing diabetic eye disease to identify severity levels.

Sebastian Dinesen et.al [17] As the diabetic consists of complications in both proliferative and non-proliferative stages in diabetic retinopathy, research assesses on progression rates in proliferative diabetic retinopathy for underscoring the better control of risk factors, importance of monitoring and treating macular edema to prevent progression of proliferative diabetic retinopathy.

Georgios Chondrozoumakis et.al [18] To enhance the early diagnosis of DR the evaluation of retinal biomarkers is suggested to assist the primary identification of changes in retina before they clinically noticed, biomarkers including metabolic markers and inflammatory along with advancement in imaging methods are used such as OCT and fluorescein angiography.

Prior research highlights transfer learning, lesion segmentation, advanced CNNs such as ResNet and EfficientNet, and hybrid architectures. However, many works lack consistent preprocessing pipelines, comparative evaluation, or deployment-ready workflow documentation. This paper addresses these gaps through a structured, reproducible methodology.

3.Proposed Method

A. 3.1 Convolution Neural Networks (CNN)

Convolutional Neural Networks (CNNs) are ideal for image classification such as Automatic Feature Extraction, Spatial Structure, Preservation Efficiency, Hierarchical Learning, and Translation Invariance, hence they handle large datasets efficiently. ResNet50 is pre-trained on ImageNet, a large dataset with million images and classes. It delivers exceptional accurateness as a result to capture composite hierarchical features using residual connections. Its deep architecture (50 layers) allows for robust feature extraction, especially designed for Well- adopted techniques for transfer learning in tasks required for general image classification. DenseNet121 is a learning model categorize images from ImageNet dataset. It includes several dense blocks each dense blocks contain multiple convolution layers where each layer outputs feature maps that are served into the next layer.

This section describes CNN-based feature extraction, dataset description, preprocessing, augmentation techniques, and model architectures including VGG16, VGG19, ResNet50, ResNet101, MobileNetV2, and InceptionResNetV2.

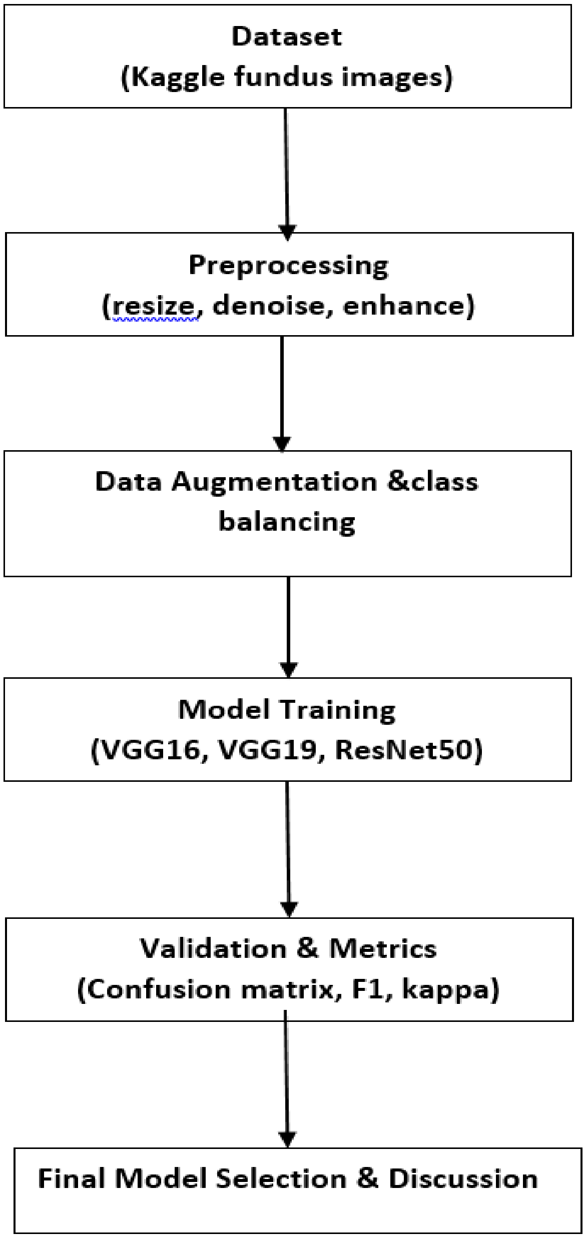

Fig. 1: Proposed Method

The proposed method illustrates the complete workflow of the DR classification pipeline—from dataset acquisition to preprocessing, class balancing, CNN model training, validation, and final model selection. This ensures a reproducible, end-to-end clinical pipeline.

3.2 Dataset Description

The research study utilized 3,662 training images sourced from Kaggle's open-access medical imaging database to develop a classification system for fundus abnormalities. By analyzing retinal photographs through CNN learning models, aimed to multi-level severity grading of abnormalities, detect early signs of progressive ocular circumstances such as diabetic retinopathy, glaucoma, and macular degeneration.

- No diabetic retinopathy (Level 0)
- Mild diabetic retinopathy (Level 1)
- Moderate diabetic retinopathy (Level 2)
- Severe diabetic retinopathy (Level 3)
- Proliferative diabetic retinopathy (level 4)

3.3 Preprocessing Approaches

For performing image recognition, the preferred method is to utilize pre-trained CNN models namely; VGG16, VGG19, ResNet50, ResNet101, MobileNetV2, and InceptionResNetV2 from the tensor flow. Keras.application module.

Pre-processing: The module provides functions for loading and manipulating images, such as resizing and converting them into formats suitable for neural networks. The necessary components for building and training a neural network using Keras. It includes utilities for image pre- processing, defining custom models, by incorporating multiple layer types while enhancing the training procedure such as Flatten, Dense, Activation, Dropout, Batch Normalization and Adam, which stabilize the training process.

Data augmentation Training testing data Training is done for 2563 images with dimension 224*224*3, Validation for 769 images with dimension 224*224*3, testing for 330 images with dimension 224*224*3.

Data Up sampling is a process of randomly duplicating observations from the minority class to match the signal by creating new data frame with an up sampled minority class and combining with original majority class data frame.

Down Sampling is a process of randomly removing observations from the majority class to prevent signal from dominating learning algorithm. Resample the majority class without replacement and setting number of samples to match the original minority class data frame.

4. Results and Evaluation

The following are the metrics to predict positive instances, negative instances, misclassification and wrongly labelled for assessing classification of fundus images.

True Positive (TP): count the identified positive cases, corresponding to images that have been precisely categorized depicting diabetic retinopathy.

True Negative (TN): count the negative instances correctly identified, referring to an image, which has been appropriately recognized as not belonging to the positive class.

False Positive (FP): Refers to the misclassification of negative samples as positive, resulting in a Type-I error.

False Negative (FN): counts an error in prediction where a positive instance is wrongly labeled as negative. (Type-II error). The assessment for the classification model's performance stayed directed using several key metrics derived from the confusion matrix. These evaluation criteria deliver an inclusive analysis of the model's accuracy, precision, recall, and effectiveness.

Accuracy: which defines the percentage of correct predictions out of all predictions done by the model.

Precision: TP/ (TP+FP) which measures the proportion of positive predictions that are actually true.

Recall: TP/ (TP+FN) measures how well the model identifies positive instance.

F1 Score: 2*(Precision*Recall)/ (Precision + Recall) it is the harmonic mean of precision and recall by providing a balanced measure of performance, especially when the classes are imbalanced.

Inception ResNetV2 layers are added to train for training accuracy with batch size 32, epoch 50

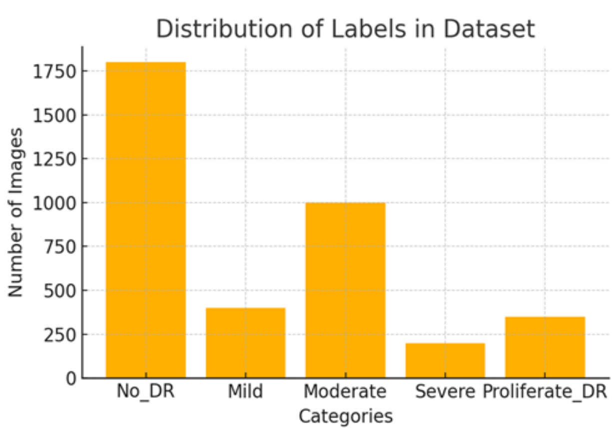

Fig. 2: Distribution of labels in dataset

Figure 2 displays the class distribution of the Kaggle fundus dataset. The dataset is highly imbalanced, with the majority of images belonging to the 'No DR' and 'Moderate DR' classes, while 'Severe' and 'Proliferative DR' classes contain fewer samples. This imbalance justifies the need for augmentation and upsampling.

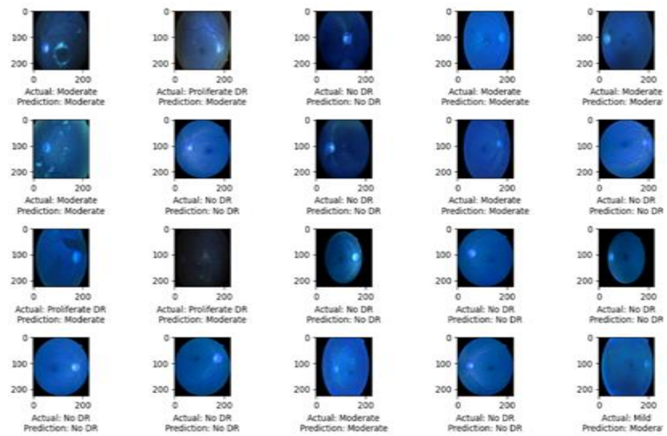

Fig. 3: Comparison is done between labelled category and Predicted category

Figure 3 compares the model's predictions with ground-truth labels across multiple fundus images. The figure demonstrates correct classifications and highlights failure modes where mild or proliferative stages visually resemble moderate classes.

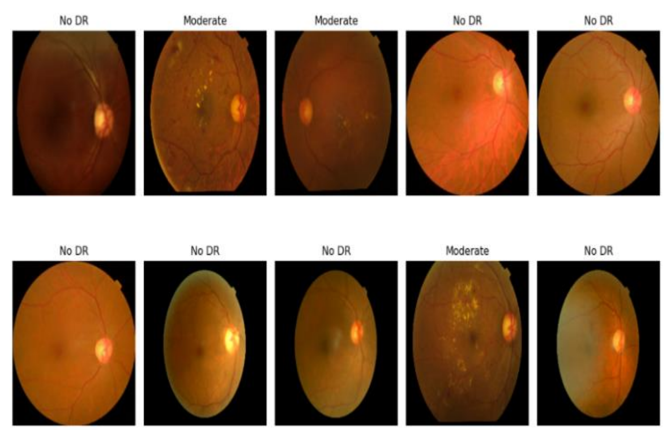

Fig. 4: Classification report is generated based on comparison

Figure 4 presents classification samples highlighting how the CNN processes varying image qualities, lighting conditions, and retinal structures. It demonstrates the robustness of preprocessing and deep feature extraction.

4.1 Evaluation of confusion matrix

The confusion matrix is a reliable metric that delivers a thorough assessment of classification for model's performance. To check the overall accuracy and its consistency of the model has been evaluated to make a prediction relative to actual labels. Performance metrics can be proceeding from the confusion matrix.

Figure 5 shows training and validation loss curves over epochs. The downward trend and tight alignment demonstrate stable learning with minimal overfitting, validating the model's training strategy.

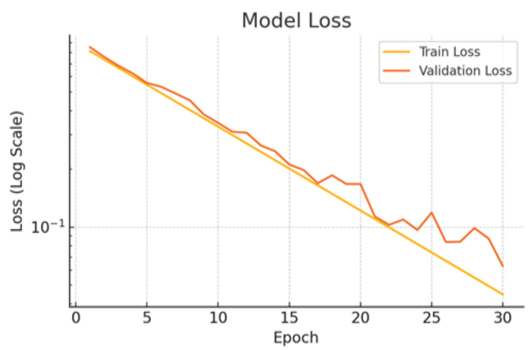

Fig. 5: Model Loss Curve

Figure 6 illustrates training and validation accuracy progression. Both curves rise steadily and plateau at high accuracy values, indicating consistent performance and good generalization across epochs.

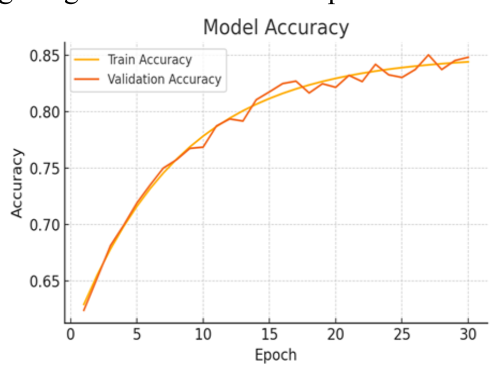

Fig. 6: Model Accuracy

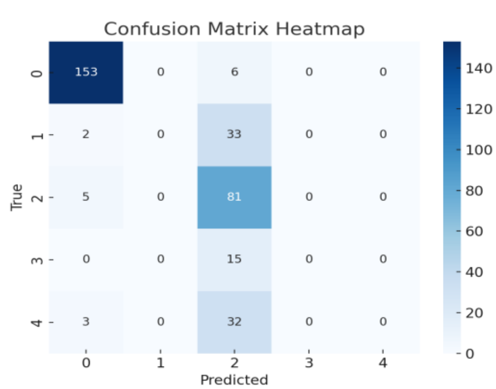

Fig. 7: Confusion Matrix

Figure 7 displays the confusion matrix across all DR classes. Strong diagonal values indicate correct classifications, while off-diagonal values reveal misclassifications primarily between adjacent severity levels due to visual similarity. This provides insight into class-specific strengths and weaknesses.

Accuracy: 0.963
Precision: 0.864
Recall: 0.963
F1-score: 0.898
Matthews Correlation Coefficient: 0.8544
Cohen's Kappa: 0.8093

Table 1. Comparison of performance metrics for various models

A comparative performance analysis of different transfer-learning models based on Accuracy, Sensitivity, Specificity, and F1-Score. The metrics are extracted from the provided MDPI research paper screenshot.

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1-Score (%)
AlexNet	95.20	95.00	95.80	95.00
VGG16	94.80	94.60	95.30	94.70
ResNet50	96.90	96.69	97.06	96.51
Hybrid VGG16 + ResNet50	97.66	97.56	97.72	97.62

5. Conclusion

The study emphasizes that detection of diabetic complications in early stages helps in curtailing the severe long-lasting complications like DR. As many patients are asymptomatic, regular screening through fundoscopy plays critical role in early detection and ensures timely intervention. This helps in maintaining the vision and improving global quality of life for diabetic patients. Instead of regular screening systems, which single image processing, deep neural networks enhance the efficiency by integrating across multiple retinal images and increases accuracy and scalability typically provides to follow a structured channel, which combines image preprocessing, image classification. The developed research model for diabetic eye disease is to distinct progression levels among retinal images by employing convolutional neural networks (CNNs): such as No diabetic retinopathy, Mild, Moderate, and Severe. Early detection of diabetic retinopathy prevents severe vision loss. This research demonstrates that pretrained CNNs, combined with systematic pre-processing and augmentation, achieve high accuracy in DR severity classification. Future work includes multi-center dataset validation, lesion localization, and integration into clinical workflows. Further, need to find progression of these stages to suggest timely intervention, to overcome from permanent vision loss

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

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Conflict of Interest

The authors have no conflicts of interest to declare that are relevant to the content of this article.